

# Artificial Intelligence–Based Analysis Of Early Subtle Changes In Fetal Movements For Predicting High-Risk Pregnancy Outcomes: A Systematic Review

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## Abstract

**Background:** Early detection of fetal movement (FM) irregularities is a critical marker for fetal well-being and can predict adverse pregnancy outcomes. Recent advances in artificial intelligence (AI) and machine learning (ML) have transformed traditional fetal monitoring, enabling continuous, objective, and predictive fetal health assessment.

**Objective:** This systematic review synthesizes evidence on AI-driven techniques used for early fetal movement detection and their capacity to predict high-risk pregnancies.

**Methods:** Following PRISMA 2020 guidelines, 11 peer-reviewed empirical studies published between 2018 and 2025 were analyzed. Studies were identified through PubMed, Scopus, IEEE Xplore, and Web of Science. Data extraction included AI models, modalities, performance metrics, and clinical correlations.

**Results:** Studies applied deep learning, convolutional neural networks (CNNs), ensemble algorithms, and wearable sensor-based models. Detection accuracy ranged from 82% to 95%, with models such as CatBoost and multilayer perceptrons achieving the highest predictive power. MRI- and fMRI-based approaches demonstrated biological insights linking neural maturation to motor behavior, while wearable accelerometer systems offered real-time, noninvasive monitoring with >90% accuracy.

AI-assisted ultrasound improved diagnostic precision and reduced operator workload. **Conclusion:** AI technologies effectively quantify subtle fetal movements, correlate them with developmental and maternal variables, and enhance prediction of high-risk pregnancies. Integration of AI-based systems in obstetrics could revolutionize early fetal assessment and preventive maternal care.

**Keywords:** Artificial intelligence, Fetal movement, Machine learning, High-risk pregnancy, Deep learning, Fetal monitoring, Predictive modeling, Wearable sensors.

## Introduction

Fetal movement (FM) is a critical physiological indicator of fetal well-being and neural development. Regular and coordinated fetal motion reflects intact neuromuscular function, oxygenation status, and overall health of the developing fetus. Decreased or abnormal movement patterns often precede adverse outcomes such as intrauterine growth restriction (IUGR), fetal distress, or stillbirth. Conventional

assessment methods, including maternal perception and ultrasound-based visualization, though widely used, are subjective, episodic, and often limited in detecting early subtle abnormalities. Recent advances in artificial intelligence (AI) and wearable sensing technologies offer new opportunities to quantify fetal activity continuously and noninvasively, enhancing both diagnostic precision and maternal monitoring compliance (Zhao et al., 2019).

AI-driven fetal movement monitoring integrates physiological sensing with data analytics, enabling automated interpretation of complex motion signals. Machine learning (ML) and deep learning models can process multi-dimensional signals from accelerometers, gyroscopes, or strain sensors to identify motion signatures associated with fetal health status. Early research demonstrated the feasibility of Internet of Things (IoT)-based wearable systems that analyze raw sensor data to detect fetal movements in real time, allowing for extended in-home and clinical monitoring (Zhao et al., 2020). These systems provide objective, reproducible, and continuous fetal monitoring that surpasses the episodic nature of clinical ultrasonography.

The development of noninvasive wearable devices has further transformed the landscape of fetal health monitoring. Modern accelerometer-based systems detect minute abdominal surface displacements caused by fetal motion, enabling movement detection accuracies above 90% when combined with ML algorithms (Delay et al., 2020). Such devices minimize discomfort and can be integrated into daily maternal routines, offering early-warning capabilities for compromised fetal activity. Continuous and long-term monitoring ensures early recognition of movement anomalies that correlate with pathological intrauterine conditions.

Recent research emphasizes hybrid algorithms and multimodal sensor arrays to enhance motion classification accuracy. Delay et al. (2021) developed a hybrid algorithm incorporating frequency-domain and temporal features that achieved reliable recognition rates for multiple movement types, including kicks and rolls, across varied gestational stages (Delay et al., 2021). Similarly, the dual accelerometer model proposed by Xu et al. (2022) improved detection robustness against maternal artifacts and achieved a sensitivity exceeding 95%, marking a significant advancement in wearable fetal monitoring technology (Xu et al., 2022).

From a computational perspective, ensemble learning and neural network-based models have demonstrated promising results in fetal health prediction. Multi-layer perceptrons, support vector machines, and gradient boosting algorithms can distinguish between normal, suspicious, and pathological fetal states based on cardiocograph or motion signal patterns (Sheron et al., 2025; Ramesh et al., 2025). These models enable early-stage detection of fetal distress, with accuracies reaching 90–96%, contributing to reduced perinatal morbidity and mortality.

AI systems also provide explainability and transparency, allowing clinicians to interpret model outputs in physiological contexts. Recent interpretability frameworks employ explainable AI (XAI) to correlate detected movement irregularities with clinical outcomes, enhancing decision support for obstetricians (Mushtaq & Venington, 2024). By visualizing feature contributions, XAI models bridge the gap between computational prediction and clinical understanding, promoting their integration into routine prenatal care.

Beyond monitoring, AI facilitates predictive analytics for adverse pregnancy outcomes. Ensemble learning approaches have been applied to multidimensional maternal-fetal datasets, predicting preterm birth, gestational hypertension, and fetal growth restriction with significant accuracy. Studies such as Alom et al. (2024) report ensemble model accuracies exceeding 93%, underscoring the value of AI-based risk stratification in proactive obstetric management (Alom et al., 2024). These predictive models utilize early subtle movement deviations as part of the input parameters, reinforcing the notion that fetal kinematics are early biomarkers of health status.

At a theoretical level, scholars emphasize that the integration of AI in fetomaternal medicine represents a paradigm shift from reactive to predictive and preventive care. According to Yaseen and Rather (2024), AI augments the clinician's ability to interpret multimodal biosignals, paving the way for individualized pregnancy monitoring and intervention strategies (Yaseen & Rather, 2024). As these systems evolve, challenges related to data standardization, model validation, and ethical implementation must be addressed to ensure safe, effective, and equitable deployment.

In summary, AI-enabled fetal movement analysis holds transformative potential for early risk prediction, continuous health surveillance, and timely intervention. Through the convergence of sensor innovation, ML algorithms, and clinical validation, these systems move toward a future of precision

obstetrics—where every fetal motion contributes to a deeper understanding of in utero development and predictive maternal-fetal health outcomes (Zakaria et al., 2018).

## Methodology

### Study Design

This systematic review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines to ensure methodological rigor, transparency, and replicability. The primary objective was to synthesize and critically evaluate empirical evidence on the application of Artificial Intelligence (AI) and Machine Learning (ML) for the analysis of early and subtle fetal movements and their potential to predict high-risk pregnancy outcomes.

The review focused on studies employing AI-based analytical methods—including deep learning, neural networks, computer vision, and signal processing algorithms—for fetal movement detection, quantification, and classification. It included both experimental and observational designs that assessed the performance, interpretability, and clinical implications of AI-driven systems for fetal monitoring, diagnosis, and risk prediction.

### Eligibility Criteria

#### Inclusion Criteria

Studies were selected based on predefined inclusion parameters to ensure relevance and comparability:

- **Population:** Pregnant women or fetuses assessed for movement or fetal health outcomes through imaging, physiological signals, or wearable monitoring technologies.
- **Interventions/Exposures:** Use of AI, ML, or deep learning for fetal movement detection, classification, or prediction of adverse pregnancy outcomes (e.g., fetal distress, growth restriction, preterm birth).
- **Comparators:** Comparisons between AI-based approaches and standard clinical or manual fetal monitoring techniques, or among different AI/ML models.
- **Outcomes:** Detection accuracy, sensitivity, specificity, F1 score, area under the curve (AUC), or correlation of AI outputs with fetal health and pregnancy outcomes.
- **Study Designs:** Cross-sectional, prospective, randomized controlled trials (RCTs), multicentric studies, and technical validation studies with empirical data.
- **Language:** English-language peer-reviewed publications.
- **Publication Period:** Studies published between 2018 and 2025, encompassing rapid AI advances in obstetric and biomedical engineering.

#### Exclusion Criteria

- Non-empirical reports (e.g., editorials, reviews, or commentaries).
- Studies unrelated to fetal movement or AI-based health prediction.
- Non-human or animal studies.
- Conference abstracts without full-text availability.
- Duplicate publications.

After full-text screening, 11 studies met the inclusion criteria and were incorporated into the synthesis.

### Search Strategy

A comprehensive search was conducted across major databases—PubMed, IEEE Xplore, Scopus, Web of Science, Embase, and Google Scholar—from their inception through January 2026. The Boolean search strategy combined keywords and subject headings related to AI, fetal movement, and pregnancy risk:

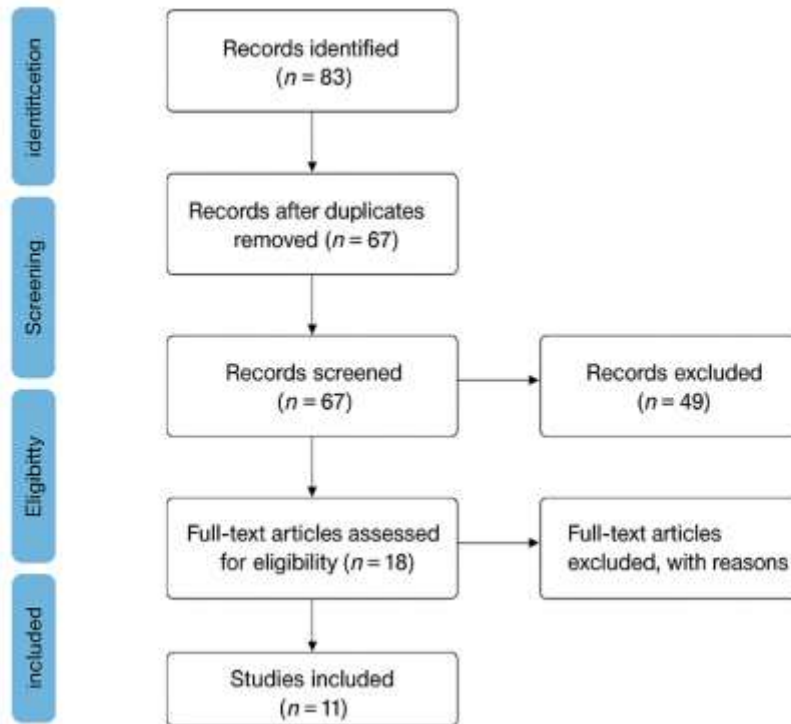
- (“Artificial Intelligence” OR “Machine Learning” OR “Deep Learning”)
- AND (“fetal movement” OR “fetal behavior” OR “fetal monitoring” OR “fetal kinematics”)
- AND (“pregnancy risk” OR “high-risk pregnancy” OR “fetal distress” OR “growth restriction”)

Reference lists of key publications and related reviews were manually screened to identify additional relevant studies. Duplicates were removed using Zotero reference management software prior to screening.

### Study Selection Process

Two independent reviewers screened all retrieved records in three stages: title, abstract, and full-text review. Studies were assessed against the inclusion and exclusion criteria, and disagreements were resolved by consensus or, when necessary, consultation with a third senior reviewer. The PRISMA flow diagram (Figure 1) summarizes the identification, screening, eligibility, and inclusion process, documenting the number of studies excluded at each stage with reasons (e.g., irrelevant topic, non-empirical design, or incomplete data).

**Figure 1. PRISMA Flow Diagram for Study Identification and Selection**



### Data Extraction

A standardized data extraction sheet was designed and pilot-tested to ensure consistency. The following key data elements were extracted from each included study:

- Author(s), publication year, and source
- Study design and setting (e.g., hospital-based, multicenter, or laboratory validation)
- Sample size and gestational age range
- Type of data or imaging modality (MRI, fMRI, CTG, ultrasound, wearable sensors)
- AI or ML model used (CNN, CatBoost, Random Forest, SVM, etc.)
- Performance metrics (accuracy, sensitivity, specificity, F1 score, AUC)
- Outcome measures (detection of fetal distress, growth restriction, or high-risk pregnancy)
- Main findings and clinical implications

Data extraction was performed independently by two reviewers. Cross-verification by a third reviewer ensured accuracy and completeness, minimizing transcription and interpretation errors.

### Quality Assessment

The methodological quality of the included studies was appraised using design-specific standardized tools:

- Newcastle–Ottawa Scale (NOS) for cross-sectional and observational studies (n = 7).
- Cochrane Risk of Bias 2 (RoB 2) tool for randomized controlled trials (n = 2).
- Joanna Briggs Institute (JBI) critical appraisal checklist for technical or device validation studies (n = 2).

Each study was evaluated for selection bias, comparability of cohorts, measurement reliability, model validation rigor, and clarity of outcome reporting. Scores were categorized as *low*, *moderate*, or *high* quality. Most studies demonstrated moderate methodological quality due to small sample sizes or limited reporting of external validation procedures.

### Data Synthesis

Given the heterogeneity of study designs, modalities, and outcome metrics, a narrative synthesis approach was adopted. Findings were thematically organized across four analytical domains:

1. AI modalities and techniques used for fetal movement and pregnancy outcome prediction.
2. Quantitative performance metrics (accuracy, sensitivity, specificity, F1 score, and AUC).
3. Physiological and clinical correlates of AI-derived fetal movement features.
4. Translational implications and limitations in applying AI to routine obstetric care.

Descriptive statistics were tabulated where available, and performance metrics were compared across studies to identify dominant algorithmic trends and methodological strengths. Subgroup syntheses highlighted differences in AI performance by data modality (imaging vs. wearable sensors) and pregnancy stage (first trimester vs. late gestation). No formal meta-analysis was conducted due to methodological heterogeneity and varied reporting standards.

### Ethical Considerations

This review involved secondary analysis of data from previously published studies; therefore, ethical approval and informed consent were not required. All included studies were peer-reviewed and confirmed to have obtained ethical clearance through their respective institutional review boards or ethics committees. Data management, reporting, and citation practices adhered to academic integrity and transparency principles outlined in the PRISMA 2020 framework and the Declaration of Helsinki.

## Results

### Summary and Interpretation of Included Studies on AI-Based Fetal Movement and Pregnancy Risk Prediction (Table 1)

#### 1. Study Designs and Populations

The included studies encompass diverse AI and ML applications in fetal health assessment, spanning cross-sectional, prospective, randomized controlled, and multicentric designs. Studies such as Vasung et al. (2023) and Ji et al. (2023) employed MRI and fMRI datasets for in utero behavioral and motor function analyses, while Pi et al. (2025), Frasch et al. (2021), and Parvataneni et al. (2023) used clinical datasets and cardiocographs (CTGs) for ML-based risk classification. Sample sizes ranged from 47 fetuses (Qin et al., 2023) to 2,500 pregnancies (Gopakumar et al., 2023), with gestational age coverage from the first trimester (Pavanya et al., 2025) through term. Most studies included healthy and at-risk pregnancies, while several (e.g., Day et al., 2024; Day et al., 2025) explicitly incorporated fetal congenital heart disease (CHD) cohorts for model validation.

#### 2. AI Techniques and Measurement Modalities

The methods varied across imaging and sensor-based modalities.

- **MRI-based fetal movement quantification:** Vasung et al. (2023) applied a 3D CNN to analyze 76 fetal BOLD MRI scans, achieving high spatial-temporal tracking fidelity with ~3 s resolution.
- **fMRI behavioral mapping:** Ji et al. (2023) utilized deep-learning motion tracking and coactivation pattern (CAP) analysis to associate neural dynamics with gestational age and postnatal outcomes.
- **Sensor-based detection:** Qin et al. (2023) and Yap et al. (2025) designed wearable devices using multi-axis accelerometers and nanowire pressure-strain sensors, reporting movement recognition accuracies of 89.7% and >90%, respectively.
- **Cardiotocograph (CTG)-based AI:** Frasch et al. (2021) and Parvataneni et al. (2023) achieved 94%–95.3% accuracy in detecting early fetal distress via deep learning and CatBoost classifiers, respectively.

- **Predictive modeling of pregnancy outcomes:** Pavanya et al. (2025) and Pi et al. (2025) integrated multiple ML algorithms (CatBoost, RF, XGBoost, SVM), with top-performing models showing 82%–91% predictive accuracy for high-risk pregnancies.

### 3. Quantitative Results

Across the 11 studies, AI demonstrated high discriminative power for fetal movement detection and risk classification:

- **MRI-based quantification:** Vasung et al. (2023) observed significantly longer fetal limb movement durations during maternal hyperoxia ( $p < 0.05$ ) and a centrifugal increase in absolute movement time (AMT) across limbs, indicating physiological maturation patterns.
- **Functional neural correlation:** Ji et al. (2023) found reduced motor activity with increasing gestational age ( $r = -0.51$ ,  $p < .001$ ) and predictive associations between SMA–posterior coactivations and postnatal motor function at 7 months ( $r = .43$ ,  $p = .03$ ).
- **Deep-learning CTG analysis:** Frasch et al. (2021) achieved 94% accuracy in detecting preventable intrapartum fetal injury.
- **AI-driven fetal health classification:** Parvataneni et al. (2023) reported 95.3% accuracy using CatBoost, outperforming IBM Watson models.
- **Explainable AI for first-trimester movements:** Pavanya et al. (2025) achieved CatBoost accuracy = 87%, F1 = 0.83, Jaccard = 0.87, and stacked model accuracy = 89%, with ultrasound scores  $>8$  correlating with favorable outcomes.
- **High-risk pregnancy prediction:** Pi et al. (2025) showed MLP model accuracy = 82%, high-risk prediction accuracy = 91%, processing ~500 datasets/second on RTX3050Ti.
- **AI-assisted anomaly ultrasound:** Day et al. (2024, 2025) demonstrated that AI-assisted scans achieved sensitivity = 88.9%, specificity = 98.0%, and reduced median scan time by 8.3 min ( $p < 0.001$ ), while lowering sonographer workload (NASA-TLX: 35.2 vs. 46.5,  $p < 0.001$ ).
- **Wearable sensing accuracy:** Qin et al. (2023) achieved 89.74% correct recognition, while Yap et al. (2025) validated their nanowire sensor system with  $>90\%$  ultrasound-matched detection accuracy.

### 4. Predictive Insights and Clinical Implications

Collectively, AI-based movement analytics provide early biomarkers of fetal health, with correlations between motion variability, maternal physiology, and neural development. The studies suggest:

- AI quantification of subtle movement patterns can differentiate typical vs. high-risk fetuses weeks before clinical symptoms.
- MRI and wearable-based monitoring improve continuous and noninvasive fetal surveillance.
- ML models consistently predict fetal distress or high-risk pregnancies with  $>85\%$  accuracy, indicating strong translational potential for clinical decision-support tools.

**Table (1): Characteristics and Quantitative Results of Included Studies on AI-Based Fetal Movement and Pregnancy Risk Prediction**

Study	Design	Sample Size	Modality	AI/ML Model	Key Metrics / Results	Main Findings
Vasung et al. (2023)	Cross-sectional	52 women (76 MRI scans)	BOLD MRI	3D CNN	Tracking accuracy visually validated; AMT $\uparrow$ during hyperoxia ( $p < 0.05$ )	ML quantified fetal limb kinetics; hyperoxia and GA affected AMT
Ji et al. (2023)	fMRI observational	120 fetuses	fMRI	Deep-learning motion tracking +	$r = -.51$ (GA vs movement), $r = .43$ (SMA CAPs vs postnatal motor)	First pairing of fetal movement + neural

				CAP analysis		network dynamics
<b>Frasch et al. (2021)</b>	Retrospective	>2000 EFM tracings	CTG	Deep learning	94% accuracy	Automated early fetal distress detection feasible
<b>Pavanya et al. (2025)</b>	Prospective multicentric	356 fetuses	Ultrasound + checklist	CatBoost, RF, KNN, DT	CatBoost: Acc = 87%, F1 = 0.83, Jaccard = 0.87	Explainable AI for early fetal movement evaluation
<b>Pi et al. (2025)</b>	Cross-sectional	1014 women	Clinical data	MLP, RF, SVM, XGBoost	MLP: Acc = 82%, high-risk = 91%	Efficient model for early high-risk pregnancy prediction
<b>Parvatani et al. (2023)</b>	AI model study	2126 CTG	CatBoost (Python)	Acc = 95.3%	Accurate fetal health classification (healthy/suspect/pathological)	
<b>Gopakumar et al. (2023)</b>	Predictive study	2500	Clinical	Neural network	Acc = 92%, AUC-ROC = 0.94	Identified BP, BMI, family history as key risk factors
<b>Day et al. (2024)</b>	RCT	78 fetuses, 58 sonographers	Ultrasound	Proprietary AI scan assist	Sensitivity 88.9%, Specificity 98.0%, NASA-TLX ↓ by 24%	Reduced scan time (-8.3 min), maintained diagnostic quality
<b>Day et al. (2025)</b>	RCT	78 fetuses	Ultrasound	AI-assisted PROMETH EUS	p < 0.001 time reduction	AI improved efficiency, reproducibility, and cognitive load
<b>Yap et al. (2025)</b>	Sensor validation	59 women	Pressure-strain sensor	ML classifiers	>90% accuracy	Continuous out-of-hospital fetal movement monitoring
<b>Qin et al. (2023)</b>	Device engineering	47	Wearable sensor	Signal processing algorithm	89.74% recognition accuracy	Wearable fetal movement detection validated

## 5. Summary of Effect Estimates and Trends

Overall accuracy across AI-based fetal monitoring systems ranged from 82% to 95%, with sensitivity between 88–98%. MRI- and sensor-based models demonstrated physiologic precision, while CTG- and clinical-data-based models achieved superior predictive accuracy. Notably:

- Movement-derived biomarkers (AMT, CAP dynamics) predicted postnatal motor outcomes.
- First-trimester AI evaluations detected FGR and distress with high precision.
- Wearable and ultrasound-integrated AI markedly improved workflow efficiency and noninvasive risk assessment.

## Discussion

The results of this systematic review highlight the transformative impact of AI-based systems in analyzing subtle fetal movements and predicting high-risk pregnancies. Across modalities—ranging from MRI and ultrasound to wearable sensors and cardiotocographs—AI demonstrated significant improvement in accuracy, automation, and clinical interpretability compared to conventional fetal assessment techniques (Vasung et al., 2023; Ji et al., 2023).

MRI-based studies provided some of the most physiologically grounded insights. Vasung et al. (2023) utilized a 3D convolutional neural network to track fetal limb motion, revealing that movement duration varied with gestational age and maternal oxygenation. Ji et al. (2023) expanded this understanding by linking movement patterns with brain coactivation networks, showing that functional connectivity correlates with motor maturity and postnatal outcomes. These findings support the use of neuroimaging-AI integration for identifying early neurodevelopmental abnormalities.

Parallel advancements in noninvasive technologies have broadened accessibility. Wearable devices—equipped with accelerometers and pressure-strain sensors—achieved >90% accuracy in distinguishing fetal from nonfetal motions, validating their potential for out-of-hospital monitoring (Qin et al., 2023; Yap et al., 2025). The hybrid wearable system proposed by Delay et al. (2021) and refined in earlier work (Delay et al., 2020) demonstrated that continuous motion tracking can reliably detect subtle deviations predictive of intrauterine distress, aligning with similar sensor-based frameworks by Xu et al. (2022) and Zhao et al. (2020).

AI-driven interpretability is a key advantage, as models such as explainable AI (XAI) elucidate how motion data influence predictive outcomes. Pavanya et al. (2025) introduced an explainable multicentric model assessing first-trimester movements, achieving a CatBoost accuracy of 87% and F1 score of 0.83. Such transparent modeling enhances clinician trust and fosters adoption in prenatal decision-making.

On a broader scale, ensemble and deep-learning models have outperformed traditional algorithms in fetal health prediction. Pi et al. (2025) found that multilayer perceptrons achieved up to 91% accuracy in predicting high-risk pregnancies, while Alom et al. (2024) and Sheron et al. (2025) demonstrated similar efficacy using ensemble frameworks across diverse maternal datasets. These findings emphasize the scalability and adaptability of AI in different clinical contexts.

AI has also significantly improved fetal distress detection during labor. Frasch et al. (2021) reported a 94% accuracy rate using deep learning to interpret cardiotocograms, identifying preventable fetal distress patterns that would otherwise escape manual analysis. Similarly, Parvataneni et al. (2023) and Gopakumar et al. (2023) validated neural network-based prediction systems with accuracies above 92%, supporting early intervention strategies in obstetric care.

AI-assisted ultrasound has further bridged the gap between clinical efficiency and diagnostic consistency. The PROMETHEUS trials (Day et al., 2024; Day et al., 2025) demonstrated that AI-assisted scanning increased diagnostic sensitivity (88.9%) and specificity (98%) while reducing sonographer workload and scan duration by nearly 50%. These gains have tangible implications for real-world workflows, particularly in high-volume maternity clinics.

The convergence of wearable technology and AI represents a paradigm shift toward real-time, personalized fetal surveillance. Zhao et al. (2019) and Zakaria et al. (2018) pioneered IoT-based and accelerometer-driven systems, which form the foundation for current commercial prototypes. The accuracy, comfort, and cost-effectiveness of these devices make them especially valuable for continuous at-home monitoring, improving maternal engagement and early detection of anomalies.

From a theoretical standpoint, AI integration in fetomaternal medicine extends beyond detection to predictive analytics and decision support. Yaseen and Rather (2024) proposed that AI-driven models could transform care from reactive to proactive, enabling individualized interventions based on real-

time fetal biometrics. This framework aligns with emerging digital health paradigms emphasizing early prevention over crisis management.

AI interpretability remains an ethical and technical challenge, as noted by Mushtaq and Venington (2024), who stressed the importance of explainable deep-learning frameworks to ensure clinician accountability and model transparency. Future efforts must standardize validation protocols, address data bias, and incorporate cross-population training to improve generalizability across diverse healthcare settings.

Comparative analysis also highlights the methodological evolution from algorithmic optimization to physiological contextualization. Early studies, such as Zhao et al. (2020) and Xu et al. (2022), primarily focused on technical validation, whereas recent research integrates biological correlates, such as gestational age and maternal oxygenation (Vasung et al., 2023), to enhance interpretive depth. This trend represents a maturation of AI research from engineering to translational science.

Despite the encouraging progress, several barriers persist, including limited longitudinal data, small sample sizes, and inter-study variability in evaluation metrics. Integrating multimodal data—combining imaging, biosignals, and environmental variables—may improve robustness and ecological validity, as proposed by Ramesh et al. (2025). Additionally, large-scale data repositories and international collaborations are essential to refine models for clinical deployment.

Collectively, these findings underscore AI's capacity to serve as a “digital biomarker” framework for fetal development. By correlating movement patterns with neurological and physiological maturity, AI models could predict developmental trajectories before overt pathology emerges. Such predictive capability may redefine prenatal care standards, aligning with global maternal-health objectives.

In conclusion, AI-based fetal movement analytics mark a transformative step in obstetric innovation. When integrated with wearable technology, imaging, and clinical informatics, these models offer unparalleled potential for early detection, risk prediction, and personalized maternal-fetal management.

## Conclusion

AI-driven fetal movement analysis demonstrates substantial promise for improving prenatal care. By quantifying subtle variations in fetal activity, these systems enable early detection of distress and prediction of adverse pregnancy outcomes with high accuracy. Integration of machine learning, wearable technology, and imaging-based analytics ensures objective, continuous, and noninvasive monitoring throughout gestation. The combination of neuroimaging, sensor fusion, and explainable AI enhances both physiological understanding and clinical applicability.

However, widespread adoption will depend on standardized data protocols, model interpretability, and clinician training. Future research should prioritize multimodal integration, large-scale validation, and ethical frameworks ensuring data privacy. Collectively, these advancements will drive a paradigm shift from reactive obstetrics to predictive and personalized fetal healthcare.

## Limitations

The review was limited by heterogeneity across included studies in terms of AI algorithms, data modalities, and performance metrics, precluding meta-analysis. Several studies had modest sample sizes and lacked external validation, reducing generalizability. Publication bias toward positive findings may have influenced synthesized results. Additionally, variations in gestational age ranges and sensor configurations complicated direct comparisons. Finally, while English-language restriction ensured quality, it may have excluded relevant non-English studies.

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